Rev. Roum. Sci. Techn.– Électrotechn. et Énerg.
Vol. 67, 4, pp. 433–438, Bucarest, 2022

OPTIMIZATION BY MORPHOLOGICAL FILTERS FOR SOLVING COMBINED ECONOMIC EMISSION DISPATCH PROBLEM

KHELIFA CHAHINEZ NOUR EL HOUDA[1], BELMADANI ABDERRAHIM[2]

Keywords: Optimization by morphological filter; Combined economic and emission problem; Emission dispatch; Economic dispatch.

This paper proposes a novel stochastic optimization approach named optimization by morphological filter (OMF) for solving the combined economic emission dispatch (CEED) problem with the valve point effect and multiple equality and inequality constraints. Four standard test systems, with and without transmission losses, are optimized to demonstrate the performance of OMF. Comparing the experimental results with various methods reported in the literature proves the high quality of OMF for solving CEED problems for small and large-scale systems.

1. INTRODUCTION

In response to the energy demand, which is growing, while reducing greenhouse gas emissions, many researchers promoted the penetration of renewable energies into the electricity production sector. To maximize the generated power of the system, the author in [1] utilized a multilevel inverter for grid-connected solar systems. Kacimi et al. [2] implemented a new combined method for tracking photovoltaic systems' global maximum power point. Dekali et al. [3] report the experimental implementation of the maximum power point of photovoltaic systems. Other researchers believe that renewable energy lacks coherence and depends upon weather conditions, even though it is cheap to produce and free of pollutants. They, therefore, concentrated on producing energy from fossil fuels while minimizing the cost and emissions of hazardous gases. This consists of the combined economic and emission dispatch problem (CEED). Since the efficiency of metaheuristic approaches has been proved, the researcher's interest has been turned to employing them for solving CEED problem.

Abido applied evolutionary algorithms such as Pareto genetic algorithm (NPGA) [4], non-dominated sorting genetic algorithm (NSGA) [5], and strong Pareto evolutionary algorithm (SPEA) [6] to solve CEED problem. Alsumait et al. [7] presented a hybrid algorithm consisting of a genetic algorithm (GA), pattern search (PS), and sequential quadratic programming (SQP) to optimize fuel cost and emission functions. The problem was also solved using a fuzzy-based bacterial foraging algorithm (MBFA) [8] and fuzzy dominance sorting bacterial foraging (FSBF) [9], which were developed based on the bacterial foraging algorithm. Differential evolution [10], evolutionary algorithm based on decomposition [11], and summation-based multi-objective differential evolution algorithm (SMODE) [12] were successfully applied to deal with CEED problem. Roy et al. [13] added the oppositional-based learning concept into the original TLBO [14] to accelerate the convergence rate to sort out the nonlinear multi-objective CEED problem, while Zou et al [15] used a new mechanism to guide the search process of the traditional particle swarm algorithm. Among others, opposition-based greedy heuristic search [16], backtracking search algorithm [17], modified artificial bee colony [18], modified NSGA-II algorithm [19], and gravitational search algorithm [20] are also recent metaheuristics that have been used to deal with the CEED problem. Maamri et al. [21] showed that GWO outperforms PSO for the economic dispatch of a hybrid system, and Kherfane et al. [22] used an intelligent algorithm to deal with CEED problem.

This paper suggests the application of a new stochastic algorithm named optimization by morphological filter (OMF) proposed by Khelifa and Belmadani [23] to solve CEED problem. The method is inspired by functional erosion, a morphological transformation mainly used in image processing. It corresponds mathematically to finding the minimum pixel combination and a kernel function (structuring element) [24]. The CEED problem is formulated by a single objective function using the price penalty factor approach [25]. OMF is investigated to solve four test systems with valve point effect while satisfying total load demand and system constraints. The results have been compared with the recent methods available in the literature. The remainder of this paper can be summarized as follows: the mathematical model of CEED is presented in Section 2. Section 3 explains the weighted sum method. The concept of optimization by the morphological filter is explained in Section 4. Simulations and results of the test systems are provided in section 5. Section 6 concludes the paper.

2. CEED PROBLEM FORMULATION

The economic emission dispatch problem is basically two objective optimization problem; the first revolves around minimizing the fuel cost in the power system and the second aims at the minimization of pollutants emission. Furthermore, it must satisfy many equality and inequality constraints.

2.1 FUEL COST FUNCTION

The fuel cost function is the sum of the fuel cost of each generator in the system with considering the valve point effect. It can be expressed [26] as:

$$\mathrm{C}=\sum_{i=1}^{n} a_i+b_iP_i+c_iP_i^2+\left|e_i\sin\left(f_i\left(P_{i\min}+P_i\right)\right)\right|, \qquad (1)$$

where a_i, b_i, c_i represent the cost coefficients, e_i and f_i reflect the effect of valve point in the i^{th} generator. P_i is the power output of unit i and P_{imin} is its lower generation limit.

2.2 EMISSION FUNCTION

The emission function of the atmospheric pollutants caused by energy production can be modeled [27] as:

Département d'Informatique, Faculté des Mathématiques et Informatique. Université des Sciences et de la Technologie d'Oran – Mohamed Boudiaf, Bp 1505, Oran el M'Naouer, Algérie.
E-mail: [1]chahinez. khelifa@univ-usto.dz [2]abderrahim.belmadani@univ-usto.dz

$$E=\sum_{i=1}^{n}\left(\alpha_i+\beta_i P_i+\gamma_i P_i^2+\mu_i \exp\left(\delta_i P_i\right)\right), \quad (2)$$

where α_i, β_i, δ_i, γ_i, μ_i are the emission coefficients of i^{th} generator.

2.3 CONSTRAINTS

The power generated must equal the sum of the power demand P_D and power losses P_L. It is represented by

$$\sum_{i=1}^{n} P_i = P_D + P_L, \quad (3)$$

and the power losses can be calculated using Kron's loss formula [28]:

$$P_L=\sum_{i=1}^{n}\sum_{i=1}^{n} P_i B_{ij} P_j+\sum_{i=1}^{n} B_{0i} P_i + B_{00}, \quad (4)$$

where P_i and P_j are the real power injections at $i^{th,}$ and j^{th} buses and B_{ij}, $B_{0i,}$ and B_{00} are loss-coefficients of the transmission loss formula.

The power output of each generator must be delimited by its minimum and maximum power permitted, and it may mathematically be expressed by:

$$P_{i\min} \le P_i \le P_{i\max}. \quad (5)$$

3. WEIGHTED SUM METHOD

Cost and emission minimization are two dissimilar problems with different dimensions ($/h and ton/h) and are contradictory. So, it is not possible to combine them into a single objective. For this reason, many researchers [29–31] adopt an unorthodox optimization technique; both objective functions are multiplied by weight factor w included between 0 and 1. Also, the emission function is multiplied by a price penalty factor σ computed as

$$F = w * C + (1-w) * \sigma * E, \quad (6)$$

$$\sigma = \frac{C_i(P_{i\max})}{E_i(P_{i\max})}. \quad (7)$$

4. OPTIMIZATION BY MORPHOLOGICAL FILTER

OMF algorithm mimics the concept of functional erosion, a morphological operation used in image processing. It consists of probing the input image with a structuring element creating an output image of the same size. The value of the output pixel is the *minimum* value of all pixels about the structuring element [32]. The structuring element used has an important impact on erosion results; the output image depends essentially on its size and shape. OMF filter is like the traditional structuring element used in image processing, where the center determines the fitness value of the objective function, and the branches are randomly generated neighbors (Fig.1).

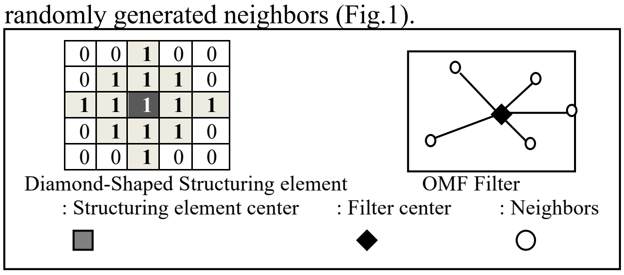

Fig. 1 – 2D Structuring element Vs OMF Filter

In addition to the search space size R, dimension D, and stop criterion ε. OMF operates by launching *Nfil* filters in the search space. Each filter has a size *fil_size*, a center C and each center has several neighbors (*Nneigh)*. The algorithm steps can be detailed below, and the analytical model is explained in Fig. 2.

Step 1: Initialize the filter centers randomly.

Initialize $C_f\left(X_f, Y_f, ...\right)$

Step 2: Generated variables are normalized using (8) to range them into the search space R and to assure that the power output of each generator is within its limits

$$C'_f\left(X_f, Y_f, ...\right)=\frac{C_f\left(X_f, Y_f, ...\right)-P_{i\min}}{P_{i\max}-P_{i\min}} * R. \quad (8)$$

Step 3: each filter center explores its neighborhood using randomly one of two options in (9). Equation (9.1) serves to enhance the exploring scale by choosing randomly to search around the actual solution (a = 0), left of the actual solution (a= -1) or right (a = 1) while (9.2) is used to explore unvisited areas

$$Neigh_i(X_i, Y_i, ...)\begin{cases} C'_f\left(X_f, Y_f, ...\right) + a * fil\_size_f \,(9.1) \\ or \\ Random * R (9.2) \end{cases} \quad (9)$$

We note here that f denotes the current filter number, and $Neigh_i$ indicates its i^{th} neighbor.

Step 4: Calculate $F(C')$, $F(Neigh)$ and store the position and fitness value of the best neighbor for each filter f if it exists

$$Best\_pos_f(X, Y, ...) = Neigh_{f,i}\left(X_i, Y_i, ...\right). \quad (10)$$

Step 5: The neighbor with the best fitness is selected to replace the original filter center (11.1), assuming that this new filter center's neighborhood may be better than the current solution's. Otherwise, the actual filter center is maintained, and its filter size is reduced to explore a closer neighborhood (11.2)

$$\begin{cases} C_f(X_f, Y_f, ...) = Best\_pos_f(X, Y, ...) \\ \text{or} \\ Fil\_size_f = \dfrac{R}{c^{k_f}} \end{cases} \quad (11)$$

Filter size is reduced by considering the previous current filer reduction k_f, and c is a constant fixed at 1.001.

Step 6: Register the position and the objective function value of the filter center that have the best fitness at this iteration and repeat 2-5 until the stop criterion is met (all filters size ≤ ε).

Set parameters: *R*, *D*, *ε*, *Nfil*, *fil_size*, *Nneigh;*
Begin
Initialize $C_f(X_f, Y_f, ..)$;
$Fil\_size_f = R;$ // f=1.. *Nfil*

$$C'_f\left(X_f, Y_f, ...\right)=\frac{C_f\left(X_f, Y_f, ...\right)-P_{i\min}}{P_{i\max}-P_{i\min}} * R;$$

REPEAT
//Explore the neighborhood by randomly perform one of the following two operations for each of the space's dimension
// a is randomly chosen in {-1, 0, 1}

$$Neigh_{f,i}(X_i, Y_i, ...) = C'_f\left(X_f, Y_f, ...\right) + a * fil\_size_f;$$

$$Neigh_{f,i}(X_i, Y_i, ...) = Random * R;$$

$$Best\_pos_f(X, Y, ...) = Neigh_{f,i}(X_i, Y_i, ...);$$

If $Best\_pos_f(X,Y,...) \neq \{\ \}$ **then**

$$C_f(X_f, Y_f,...) = Best\_pos_f(X,Y,...);$$

Else $Fil\_size_f = \frac{R}{c^{k,f}};$

Until $Fil\_size \leq \varepsilon$,// f = 1... *Nfil*

Sort all the filters by fitness value and deduce the global optimum;

End.

Fig. 2 – Pseudo code of OMF algorithm

6. RESULTS AND DISCUSSION

To validate the proposed approach's performance and assure its optimization efficiency, OMF is implemented to solve the CEED problem with the valve point effect. Delphi software is used to simulate the CEED problem, and it is implemented on a personal computer I3, with 1.7 GHz and 4 GB RAM. Four standard test systems with and without transmission losses are optimized to demonstrate the performance of OMF. We optimize each test system's fuel cost objective and emission function by fixing the weight w as 1 or 0, respectively, in (6). Here w is equal to 0.5 for CEED problem to give the same priority to both objective functions. C denotes the cost minimization, E is the emission function, and F is the total cost function for the CEED problem.

The abbreviation NA corresponds to" Not available". We note here that R is fixed at 100 and the other Parameters are fixed after many tests and we have opted for those which give the best results in term of objective function and computational time.

6.1 TEST SYSTEM 1

The problem evaluated in this case is the standard IEEE 30-bus system with six-generators. The generation capacities as well as the data of the optimization problem are taken from [32]. Moreover, the system base is 100 MVA and the total system demand for the 21 load buses is 2.834 (per unit). In this case, we opt for $\varepsilon = 10^{-9}$, *Nfil* = 5 and neighbors *Nneigh* = 2. Also, the emission equation is modestly different from (2) and it can be defined as:

$$E = \sum_{i=1}^{n} \left[0.01(\alpha_i + \beta_i P_i + \gamma_i P_i^2 + \mu_i \exp(\delta_i P_i)) \right]. \quad (12)$$

The results of the proposed approach are compared with those of NGSAII+DCD [19], SMODE [12], NGSAII [5] and MOEA/D [11]. Tables 1 and Table 2 show that the success rate of OMF is quite high for both cost and emission minimization within a time interval of 2 to 3 seconds. Figure 3 summarizes the results provided by OMF for solving CEED problem compared with NPGA [4], SPEA [6], MBFA [8] and FSBF [9]. OMF achieves the lower total cost function F = 1491.415 (C = 624.886, E = 0.197) compared to its competitors.

Tabl 1

Cost minimization of test system 1

Unit	NGSAII+ DCD[19]	SMODE [12]	NGSAII [5]	MOEA/D [11]	OMF
1	0.114	0.173	0.194	0.179	0.104
2	0.303	0.356	0.332	0.371	0.286
3	0.604	0.740	0.748	0.694	0.594
4	0.980	0.595	0.597	0.591	0.997
5	0.516	0.591	0.591	0.589	0.517
6	0.352	0.402	0.396	0.435	0.358
L	0.022	0.035	0.035	0.029	0.022
C	608.128	619.070	619.190	619.530	**605.135**
E	0.220	0.203	0.215	0.202	0.222
T	NA	NA	NA	NA	2.684

Table 2

Emission minimization of Test system 1

Unit	NGSAII+ DCD[19]	SMODE [12]	NGSAII [5]	MOEA/D [11]	OMF
1	0.410	0.398	0.409	0.406	0.415
2	0.461	0.460	0.469	0.459	0.460
3	0.553	0.542	0.542	0.550	0.541
4	0.389	0.405	0.391	0.385	0.399
5	0.545	0.545	0.540	0.545	0.542
6	0.516	0.514	0.514	0.518	0.514
L	0.033	0,0254	0.027	0,02478	0.037
C	645.647	635.990	644.970	644.980	646.073
E	0.194	0.194	0.194	0.194	0.194
T	NA	59.73	69.98	NA	**3.292**

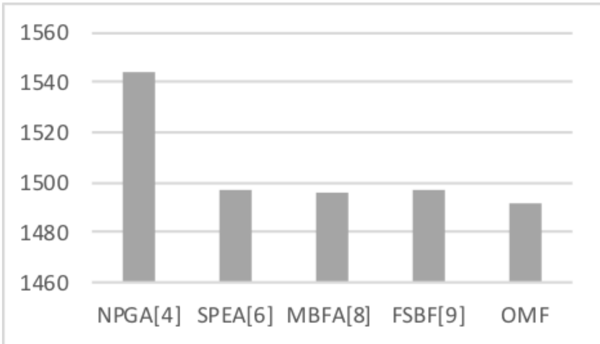

Fig. 3 – Fuel cost and emission minimization of test system 1

6.2 TEST SYSTEM 2

Six unit's system with transmission losses and load demand equal to 1200 MW is considered in this case. The input data are taken from [20]. The loss coefficient matrix can be found in [33]. OMF parameters are fixed as follow: $\varepsilon = 10^{-12}$, *Nfil* = 3, *Nneigh* = 2. Table 3 and Table 4 outline the fuel cost and emission minimization respectively.

The results obtained are compared with those of TLBO [14], QTLBO [13], DE [10] and NGPSO [15]. OMF provides very competitive result regarding the minimization of fuel cost and emission minimization separately. Furthermore, it can surpass TLBO, QTLBO, MODE [31] and OGHS [14] for solving CEED problem (F = **125382.204, C =** 66008.623, E = 1241.370) with the best computational time T = **1.139** (Fig. 4) which allows us to recommend OMF for small-scale CEED problems.

Table 3

Cost minimization of Test system 2

Unit	TLBO [14]	QTLBO [13]	DE [10]	NGPSO [15]	OMF
1	80.617	79.555	84.435	80.755	80.756
2	92.406	88.898	93.364	87.691	87.689
3	210.000	210.000	225.000	210.000	210.000
4	225.000	224.994	210.000	225.000	225.000
5	324.986	324.971	325.000	325.000	325.000
6	320.163	324.998	315.000	325.000	325.000
L	53.172	53.172	NA	53.446	53.445
C	64032.00	63977.00	64083.00	63975.77	63975.561
E	1353.100	1360.100	1345.600	NA	1360.065
T	2.09	**1.74**	8.32	NA	2.433

Table 4

Emission minimization of test system 2

Unit	TLBO [14]	QTLBO [13]	DE [10]	NGPSO [15]	OMF
1	125.000	125.000	125.000	125.000	124.909
2	150.000	150.000	150.000	150.000	150.000
3	201.466	201.268	201.182	201.268	202.831
4	199.280	199.370	199.545	199.369	199.385
5	287.963	287.971	287.619	287.971	286.422

6	286.444	286.550	286.814	286.550	286.514
L	50.154	50.159	50.160	50.159	50.064
C	65992.00	65993.00	65991.00	NA	65991.215
E	1240.700	1240.600	1240.700	1240.7	1240.636
T	1.97	1.68	8.56	NA	**1.139**

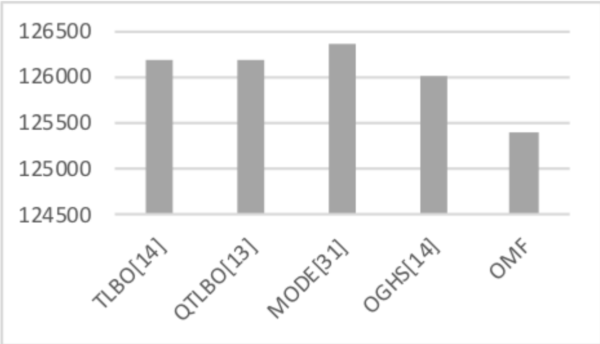

Fig. 4 – Fuel cost and emission minimization of Test system 2

6.3 TEST SYSTEM 3

This case studies a ten-unit system with P_D = 2000MW. Data units and the loss coefficients are as in [13]. This test case is investigated using a precision $\varepsilon = 10^{-9}$, *Nfil* =10 and *Nneigh* is set to 3. Comparisons of best compromising results achieved by TLBO [14], QTLBO [13], OGHS [16] and DE [10] illustrated in Tables 5 and 6.

Table 5

Cost minimization of test system 3

Unit	TLBO [14]	DE [10]	OGHS [16]	QTLBO [13]	OMF
1	55.000	55.000	55.000	55.000	55.000
2	80.000	79.806	80.000	79.999	80.000
3	105.962	106.962	106.992	107.923	105.950
4	99.932	102.831	100.535	98.648	99.983
5	80.642	82.242	81.445	82.018	82.809
6	85.788	80.435	83.067	83.488	82.032
7	300.000	300.000	300.000	300.000	300.000
8	340.000	340.000	400.000	340.000	340.000
9	469.698	470.000	470.000	469.971	470.000
10	469.999	469.898	469.898	469.999	470.000
C	87.021	87.173	146.935	87.045	85.774
E	111500	111500	111490	111498	**111417.293**
F	4563.3	4581.0	4572.274	4568.7	4586.635
T	3.23	9.42	NA	2.98	**2.913**

Table 6

Emission minimization of Test system 3

Unit	TLBO [14]	DE [10]	OGHS [16]	QTLBO [13]	OMF
1	55.000	55.000	55.000	55.000	55.000
2	80.000	80.000	80.000	80.000	80.000
3	81.126	81.134	80.592	81.126	73.681
4	81.363	81.364	81.023	81.364	82.926
5	160.000	160.000	160.000	160.000	160.000
6	240.000	240.000	240.000	240.000	240.000
7	294.479	292.743	294.507	294.479	293.914
8	297.244	299.121	297.262	297.244	297.658
9	396.804	394.515	396.735	396.804	396.051
10	395.579	395.579	395.572	395.579	395.883
C	81.595	79.456	80.690	81.595	75.111
E	116412	116400	1164100	116412	116051,52
F	3932.200	3932.400	3932.242	3932.200	**3931.017**
T	3.11	8.56	NA	2.86	**2.262**

Minimum fuel cost and minimum emission obtained by OMF for this test case are 111417.2927 ($/h) and 3931.01714 (ton /h) respectively which is much lesser than its competitors. Figure 5 recapitulates the outputs given by OMF for CEED problem as well as TLBO [14], QTLBO [13], OGHS [16] and GSA [20]. OMF produced a better optimal solution (F = **216143.454, C =** 116135.606, E = 3960.676) with a computing time less than 3 seconds. Moreover, the equality and inequality constraints are respected.

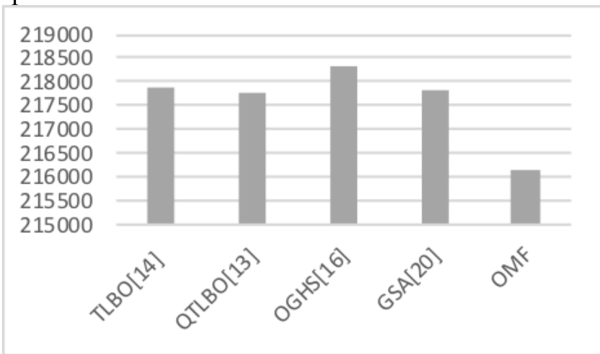

Fig. 5 – Fuel cost and emission minimization of Test system 3

6.4 TEST SYSTEM 4

This case considers 40 generators as a large-scale power system. P_D = 10500 MW, the cost and emission functions coefficients are taken from [15]. OMF parameters are fixed as follows: $\varepsilon = 10^{-59}$, *Nfil* = 2, *Nneigh* = 2. Table 7 and 8 highlight the outputs for the cost and emission minimization.

Table 7

Cost minimization of Test system 4

Unit	TSAGA [34]	TLBO [14]	DE [10]	GA-PS-SQP [7]	OMF
1	114.000	110.868	110.800	110.970	113.355
2	111.040	111.068	110.800	111.020	113.355
3	97.300	97.633	97.400	120.000	97.398
4	179.600	179.774	179.733	179.730	179.733
5	90.721	88.272	87.800	88.270	91.270
6	140.000	140.000	140.000	140.000	139.965
7	260.060	259.630	259.600	259.600	259.664
8	285.870	284.591	284.600	284.600	284.600
9	284.770	284.671	284.600	284.600	284.606
10	130.000	130.096	130.000	130.000	130.000
11	94.000	168.801	94.000	168.800	94.000
12	168.380	168.352	94.000	168.800	168.809
13	214.450	304.425	214.760	214.760	125.000
14	394.010	214.786	394.279	394.280	394.253
15	394.270	484.177	394.279	304.520	394.307
16	304.570	304.844	394.279	304.520	394.283
17	489.280	489.198	489.279	489.280	489.285
18	489.560	489.467	489.279	489.280	489.283
19	511.290	511.451	511.279	511.280	511.300
20	511.270	511.289	511.279	511.280	511.284
21	523.230	523.244	523.279	523.280	523.288
22	523.630	523.275	523.279	523.280	523.290
23	523.820	523.400	523.279	523.280	523.296
24	523.620	523.329	523.279	523.280	523.263
25	523.330	523.382	523.279	523.280	523.271
26	523.680	523.275	523.279	523.280	523.291
27	10.000	10.068	10.000	10.000	10.000
28	10.000	10.018	10.000	10.000	10.000
29	10.160	10.103	10.000	10.000	10.000
30	87.870	90.550	87.800	88.660	91.249
31	190.000	190.000	190.000	190.000	189.925
32	190.000	190.000	190.000	190.000	189.994
33	190.000	190.000	190.000	190.000	189.964
34	165.230	164.902	164.800	164.800	164.831
35	200.000	164.861	19.398	200.000	199.861
36	200.000	164.921	200.000	200.000	199.963
37	110.000	110.000	110.000	110.000	109.789
38	110.000	110.000	110.000	110.000	109.796
39	110.000	110.000	110.000	110.000	109.903
40	510.980	511.279	511.279	511.280	509.276
C	121463.070	121685.000	121837.000	121458.140	**121443.341**
E	NA	364593.6	374790.5	NA	358843.175
T	NA	**4.83**	13.25	46.98	75.473

Table 8

Emission minimization of Test system 4

Unit	BSA [17]	TLBO [14]	DE [10]	MABC [18]	OMF
1	114.000	110.868	114.000	114.000	114.000
2	114.000	114.000	114.000	114.000	114.000
3	120.000	120.000	120.000	120.000	119.595
4	169.368	169.276	169.293	169.368	169.595
5	97.000	97.000	97.000	97.000	96.384
6	124.257	124.291	124.283	124.257	124.550
7	299.711	299.718	299.456	299.711	299.036
8	297.915	297.922	297.855	297.914	297.385
9	297.260	297.257	297.133	297.259	297.602
10	130.000	130.201	130.000	130.000	130.000
11	298.410	298.388	298.598	298.409	298.819
12	298.026	298.268	297.723	298.025	298.701
13	433.558	433.566	433.747	433.556	432.999
14	421.728	421.311	421.953	421.727	421.133
15	422.780	422.576	422.628	422.778	422.350
16	422.780	422.458	422.951	422.778	422.000
17	439.413	439.516	439.258	439.412	439.961
18	439.403	439.410	439.441	439.402	439.178
19	439.413	439.295	439.491	439.412	439.843
20	439.413	439.738	439.619	439.412	439.782
21	439.446	439.543	439.225	439.445	439.696
22	439.446	439.536	439.682	439.445	439.463
23	439.772	439.218	439.876	439.771	439.209
24	439.772	439.924	439.894	439.771	439.300
25	440.112	440.380	440.440	440.111	440.787
26	440.112	439.994	439.841	440.111	440.466
27	28.994	28.993	28.776	28.993	29.125
28	28.994	29.012	29.075	28.993	29.600
29	28.994	29.060	28.904	28.993	28.698
30	97.000	97.000	97.000	97.000	97.000
31	172.332	172.306	172.404	172.331	172.388
32	172.332	172.346	172.396	172.331	172.764
33	172.332	172.464	172.314	172.331	172.645
34	200.000	200.000	200.000	200.000	200.000
35	200.000	200.000	200.000	200.000	200.000
36	200.000	200.000	200.000	200.000	199.930
37	100.838	100.947	100.877	100.838	100.663
38	100.838	100.825	100.900	100.838	100.824
39	100.838	100.890	100.778	100.838	100.644
40	439.413	439.375	439.189	439.412	439.866
C	129995.271	129952.000	129961.000	129990.000	129953.605
E	176682.265	176683.500	176683.500	176679.424	**176436.723**
T	NA	**4.63**	14.09	NA	5.944

It can be observed that the proposed approach provides better results compared with TSAGA [34], TLBO [14], DE [10], and GA-PS-SQP [7] in terms of cost minimization. OMF can achieve a difference of 14.79955 $/h compared with GA-PS-SQP, which is equivalent to 355.7895$ per day. Besides, OMF can achieve very competitive results in terms of emission minimization compared with BSA [17], TLBO [14], DE [10], and MABC [18]. It overcomes MABC with 242.7009 tons/h. Figure 6 outlines the optimum solution for the CEED problem using OMF (F = 168384.584, C = 129387.030, E = 80251.070) compared with other techniques reported in the literature as TLBO, QTLBO, MODE, and GSA.

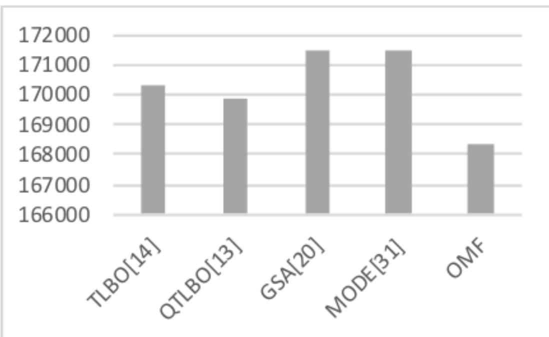

Fig. 6 – Fuel cost and emission minimization of test system 4

7. CONCLUSIONS

This paper applies the optimization by morphological filter algorithm (OMF) to solve the combined economic emission dispatch. Four test systems were investigated to illustrate the performance of the proposed approach compared with other methods reported in literature. The numerical results obtained show that OMF is efficient for solving small scale as well as large scale CEED problems in short span of time. It can satisfy all system constraints with or without valve point effect, loss or lossless. Since OMF is based on morphological filters, its parameters are easy to understand and to adjust. OMF is suitable to solve other several optimization problems.

Received on 3 January 2021

REFERENCES

1. A. Talha, A. Kouzou, A. Guichi, F. Bouchafaa, *Multilevel inverter for grid-connected photovoltaic systems*, Rev. Roum. Sci. Techn. – Électrotechn. et Énerg., Rev. Roum. Sci. Techn. – Électrotechn. et Énerg, **67**, 2, pp. 105–110 (2022).
2. N. Kacimi, A. Idir, S. Grouni, M. Boucherit, *A new combined method for tracking the global maximum power point of photovoltaic systems,* Rev. Roum. Sci. Techn. – Électrotechn. Et Énerg., **67**, *3*, pp. 349–354 (2022).
3. Z. Dekali, L. Baghli, A. Boumediene, *Experimental implementation of the maximum power point tracking algorithm for a connected wind turbine emulator*, Rev. Roum. Sci. Techn. – Électrotechn. et Énerg., **66**, *2*, pp. 111–117 (2021).
4. M.A. Abido, *A niched pareto genetic algorithm for environmental/ economic power dispatch*, Electr. Power Syst. Res. pp. 97–105 (2003).
5. M.A. Abido, *A novel multiobjective evolutionary algorithm for environmental/economic power dispatch*, Electr. Power Syst. Res. pp. 71–81 (2003).
6. M.A. Abido, Environmental/economic *power dispatch using multiobjective evolutionary algorithms, IEEE Trans. Power Syst.* pp. 1529–1537 (2003).
7. J.S Alsumait, J.K Sykulski, A.K. Al-Othman, *A hybrid GA–PS–SQP method to solve power system valve-point economic dispatch problems*, Applied Energy, **87**, *3*, pp. 1773-1781 (2010).
8. P.K. Hota, A.K. Barisal, R. Chakrabarti, *Economic-emission load dispatch through fuzzy based bacterial foraging algorithm*, Electr. Power Energy Syst., **32**, *7*, pp. 794–803 (2010).
9. B.K. Panigrahi, V. Ravikumar Pandi, S. Das, et al. *Multiobjective fuzzy dominance based bacterial foraging algorithm to solve economic emission dispatch problem,* Energy, **35**, *12*, pp. 4761–70 (2010).
10. A. El Ela, M.A. Abido, S.R. Spea, Differential *Evolution algorithm for emission constraint economic power dispatch problem*. Electr. Power Syst. Res., **80**, *10*, pp. 1286-1292 (2010).
11. Y.S. Zhu, J. Wang, *Multi-objective economic emission dispatch considering wind power using evolutionary algorithm based on decomposition*, Electr. Power Energy Syst. **63**, p. 434–445(2014)
12. B.Y. Qu, J.J. Liang, Y.S. Zhu, Z.Y. Wang, P.N. Suganthan, *Economic emission dispatch problems with stochastic wind power using summation based multi-objective evolutionary algorithm*, Inform. Sci., **351**, pp. 48–66 (2016).
13. P.K. Roy, S. Bhui, *Multi-objective quasi-oppositional teaching learning-based optimization for economic emission load dispatch problem*, Int. J. Electr. Power Energy Syst., **53**, *4*, pp. 937–48 (2013).
14. P.K. Roy, C. Paul, S. Sultana, *Oppositional teaching learning-based optimization approach for combined heat and power dispatch*, Int. J. Electr. Power Energy Syst., **57**, pp. 392–403 (2014).
15. D. Zou, L. Steven, L. Zongyan, K. Xiangyong, *A new global particle swarm optimization for the economic emission dispatch with or without transmission losses*, Energy Conversion and Management, **139**, pp. 45–70 (2017).
16. M. Singh, J.S. Dhillon, *Multiobjective thermal power dispatch using opposition based greedy heuristic search*, Int. J. Electr. Power Energy Syst., **82**, pp. 339–353 (2016).
17. M. Modiri-Delshad, N.A. Rahim, *Multi-objective backtracking search algorithm for economic emission dispatch problem,* Appl. Soft. Comput., **40**, pp. 479–494 (2016).
18. D.C Secui, *A new modified artificial bee colony algorithm for the economic dispatch problem*, Energy Conversion and Management, **89**, pp. 43–62 (2015).
19. S. Dhanalakshmi, S. Kannan, K. Mahadevan, S. Baskar, *Application of modified NSGA-II algorithm to Combined Economic and Emission Dispatch problem*, International Journal of Electrical

Power & Energy Systems, **33**, *4*, pp. 992–1002 (2011).

20. U. Güenç, Y. Sömez, S. Duman, N. Yöerükeren, *Combined economic and emission dispatch solution using gravitational search algorithm*, Sci. Iranica, **19**, *6*, pp. 1754–1762 (2012).
21. M. Maamri, MN. Tandjaoui, H. Bouzeboudja, *La methode des essaims de particules et celle du loup gris pour l'optimisation d'un systeme hybride d'energie renouvelable en Algerie,* Rev. Roum. Sci. Techn.– Électrotechnique et Énergétique, **65**, *3–4*, pp. 205–210, (2020).
22. R. Kherfane, M. Khodja, N. Kherfane, *Intelligent algorithm solutions to economic dispatch with multiple fuels and non-smooth cost function*, Rev. Roum. Sci. Techn. – Électrotechn. et Énerg, **61**, 1, p. 32–36 (2016).
23. C. Khelifa, A. Belmadani, *A new approach to continuous optimization: optimization by morphological filters*, 7th International Conference on Metaheuristics and Nature Inspired computing, Merrakech (2018).
24. B.T. Sagar, D. Kulhare, M.D. Nirmal, G. Prajapati, *Image Processing (IP) through erosion and dilation methods*, Int. J. of Emerging Technology and Advanced Engineering, **3**, *7*, pp. 285-289 (2013).
25. S. Sayah, A Hamouda, A. Bekrar. *Efficient hybrid optimization approach for emission-constrained economic dispatch with nonsmooth cost curves*. Electric Power Energy Syst, **56**, pp. 127–139 (2014).
26. I. Ziane, F. Benhamida, A. Graa, *Economic/emission dispatch problem with valve-point effect,* Rev. Roum. Sci. Techn. – Électrotechn. et Énerg, **61**, *3*, pp. 269–272 (2016).
27. M.Younes, M. Rahli, M.Abid, M.Kandouci, *Optimal power flow by intelligent algorithms,* Rev. Roum. Sci. Techn. – Électrotechn. et Énerg., **52**, *1*, pp. 3–12 (2007).
28. A.S. Tomar, H.M. Dubey, M. Pandit, *Advances in intelligent systems and computing*, Venkata Rao R., Taler J, Inc, Singapore, pp. 809–818 (2020).
29. A.L. Stanzani, A. Balbo, L. Nepomuceno, E. Baptista, *Solving the multi-objective environmental/economic dispatch problem using weighted sum and econstraint strategies and a predictor-corrector primal-dual interior pointmethod*, J. Control Autom. Electr. Syst., **25**, *4*, pp. 503–15 (2014).
30. A.M. Jubril, O.A. Olaniyan, O.A. Komolafe, P.O. Ogunbona, *Economic emission dispatch problem: a semi-definite programming approach*, Appl. Energy, **134**, pp. 446–55 (2014).
31. Q. Qin, S. Cheng, X. Chu, X. Lei, Y. Shi. *Solving nonconvex/non-smooth economic load dispatch problems via an enhanced particle swarm optimization,* Appl. Soft. Computing, **59**, pp. 229–242 (2017).
32. X. Xin Shen, D. Zou, X. Zhang, Q. Zhang, *A phase-based adaptive differential evolution algorithm for the economic load dispatch considering valve-point effects and transmission losses,* Mathematical Problems in Engineering (2018).
33. S. Agrawal, B.K. Panigrahi, M.K. Tiwari, *Multiobjective particle swarm algorithm with fuzzy clustering for electrical power dispatch,* IEEE Trans. Evol. Comput., **12**, *5*, pp. 529–541 (2008).
34. B. Mandal, PK. Roy, S. Mandal, *Economic load dispatch using krill herd algorithm*, Int. J. Electr Power Energy Syst., 57, pp. 1–10 (2014).
35. M. Basu, *Economic environmental dispatch using multi-objective differential evolution*, Appl. Soft. Comput., **11**, *2*, pp. 2845–53 (2011).
36. P. Subbaraj. P, Rengaraj. R, Salivahanan. S, *Enhancement of self-adaptive real-coded genetic algorithm using Taguchi method for economic dispatch problem*, Appl. Soft. Computing, **11**, pp. 83–92 (2011).